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# Enhancing Operational Efficacy of Smart Parking Facilities through Intelligent License Plate Recognition

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## ABSTRACT

Rapid population expansion and urbanization have increased car ownership, raising security concerns and parking issues. Safe parking is in high demand as car use rises, making sustainable urban growth challenging. Recent advances in artificial intelligence have made license plate identification and retrieval significant. Therefore, intelligent license plate identification systems are crucial for smart parking facility management. This innovative system could improve smart parking management and reduce car parking issues. Using automated license plate recognition technology decreases the time spent finding a suitable place for parking. Hence, the primary objective of this research is to introduce a proposed methodology for the recognition of car license plates, with the aim of enhancing the operational efficacy of smart parking facilities. To achieve this objective, two methodologies, namely Inpainting and Super Resolution, were employed in conjunction with the UNet and SRCNN algorithms. The proposed approach was evaluated on a comprehensive dataset comprising 4171 instances of Persian license plates. To evaluate the effectiveness of the models, several performance metrics were employed. The findings revealed that the U-Net model, incorporating a kernel regularizer, exhibited satisfactory performance, achieving an accuracy of 0.79. Similarly, the Super-Resolution Convolutional Neural Network (SRCNN) model, also utilizing a kernel regularizer, demonstrated a commendable accuracy of 0.85. Furthermore, the proposed intelligent approach in this research can be a valuable tool in the realms of inpainting and super resolution, particularly within the domain of smart parking.

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# 1. Introduction

In the contemporary landscape, proper use of energy, the exponential growth of the populace, and the corresponding escalation in vehicular presence on roadways have engendered a formidable quandary concerning the judicious utilization of parking facilities [1–3]. Also, studies have been done in relation to the use of energy harvesting devices with regard to environmental oscillating systems to supply the required electricity in the car [4,5]. Consequently, the imperative for an optimal parking management framework has become increasingly apparent. The intricate task of regulating vehicular traffic flow and ascertaining the legitimacy of vehicles seeking entry into parking lots has proven to be a multifaceted endeavor, often necessitating the deployment of specialized personnel to monitor and enforce pertinent regulations [6]. To effectively tackle these challenges, the development of an intelligent parking system has assumed utmost significance. This system would harness advanced technologies to aptly administer parking spaces, ensuring the highest degrees of precision, efficiency, and cost-effectiveness [7,8]. By leveraging cutting-edge sensors, real-time data analysis, and automated processes, this sophisticated framework would streamline the parking experience for both motorists and parking facility operators alike. The precise identification of vehicle license plate numbers holds considerable significance within the domain of smart parking facilities, as it directly influences the operational efficiency and effectiveness of parking gates and automated ticketing systems [9,10]. Nonetheless, license plates can become illegible for a variety of reasons. License plates may undergo intentional or unintentional distortion, resulting in their unreadability to the human eye or rendering them exceptionally challenging to discern. Consequently, artificial intelligence (AI), as an integral facet of human existence, has emerged as an efficacious means of resolving this predicament [11,12].

AI-driven license plate recognition systems have revolutionized the process of discerning vehicles by extracting textual information from recorded images of license plates [13,14]. These systems harness advanced algorithms and machine learning techniques to accurately interpret distorted or obscured license plate data. By seamlessly integrating AI capabilities into the infrastructure of parking management, these systems adeptly regulate the ingress and egress of vehicles from parking lots. The application of AI in the realm of license plate recognition has garnered considerable attention, resulting in invaluable and groundbreaking investigations in this field. Researchers and technologists have dedicated substantial efforts to enhance the precision, swiftness, and resilience of these systems. They have developed sophisticated AI models that proficiently process license plate images, even under arduous conditions such as low illumination, inclement weather, or intricate backgrounds [15,16]. The advancements witnessed in AI-based license plate recognition systems have far-reaching implications for smart parking. These systems not only ensure seamless and dependable access control but also facilitate efficient data management and analysis. By automatically capturing and storing license plate information, operators of parking lots can generate invaluable insights into traffic patterns, parking durations, and usage statistics [17,18]. This information facilitates judicious decision-making, enabling the optimization of parking lot operations, resource allocation, and revenue management. Furthermore, AI-driven license plate recognition systems bolster security and accountability. By accurately identifying vehicles, these systems contribute to thwarting

unauthorized access and potential breaches of security [19,20]. Moreover, they furnish a dependable audit trail by documenting vehicle entry and exit, a feature that proves indispensable in investigations or the resolution of disputes. To conclude, the integration of artificial intelligence into license plate recognition systems has proven to be a transformative development within the realm of smart parking. These systems enable efficient and precise identification of vehicles, thereby ensuring seamless processes for entry and exit while providing invaluable data-driven insights for parking management. As ongoing research and development efforts continue to augment the capabilities of AI, the future holds immense potential for further progress in license plate recognition technology, leading to a continual enhancement of the overall parking experience and the efficacy of parking lot operations [21,22].

Upon careful examination of previous studies, it is apparent that there is a pressing need for continued research dedicated to the advancement of license plate recognition systems with the aim of improving their accuracy. The recent, significant expansion in the field of artificial intelligence technology and methodologies presents conducive opportunities for extensive research in this domain.

Additionally, the review of past scholarly work indicates that, despite the valuable contributions already made, there are persistent difficulties and challenges that hinder the progress of this research. Some of these challenges include the following:

- Limitations in Current Parking Management: This study mentions the challenges related to managing parking facilities effectively, including the regulation of vehicular traffic flow and verifying the legitimacy of vehicles seeking entry. This suggests a gap in efficient, automated solutions for parking management.
- Problems with License Plate Recognition: This work notes that license plates can become illegible due to various reasons, making them difficult to read or discern. This indicates a need for more robust and reliable license plate recognition systems.
- Need for Intelligent Parking Systems: We emphasize the significance of developing intelligent parking systems that can handle these challenges effectively, implying that current solutions may not be fully adequate or intelligent.

Consequently, the principal aim of this study is to suggest a methodology for the recognition of damaged license plates, which is anticipated to substantially aid in the administration of smart parking lots. The proposed method is expected to exhibit considerable advantages in multiple case studies related to license plate recognition in smart parking management. Consequently, this research study's primary goal and contributions are as follows:

- Proposing a New Approach for License Plate Recognition: The main contribution of this paper is the proposal of a new system for identifying license plates, particularly those that are damaged or otherwise difficult to read. This system could greatly enhance the efficiency of smart parking facilities by making it easier to track and manage vehicles.
- Applying Advanced Machine Learning Techniques: Two advanced machine learning algorithms are used, namely UNet and SRCNN. These algorithms could help improve accuracy in license plate recognition, thus contributing to the field of intelligent transportation systems and smart parking.

- Evaluation of the Proposed System: The study presents a comprehensive evaluation of the proposed system, using a dataset of 4171 instances of Persian license plates. We used several performance metrics and demonstrated that our approach achieved satisfactory performance. This rigorous evaluation not only validates the proposed system but also provides a benchmark for future research in this area.
- Contributions to Sustainable Urban Planning: By improving the operational efficiency of smart parking facilities, this research could indirectly contribute to sustainable urban planning. Efficient parking management can help reduce traffic congestion, lower carbon emissions, and improve the overall quality of life in urban areas.

The organization of this study is structured as follows: Section 2 provides a comprehensive review of pertinent literature. Subsequently, in Section 3, the research methodology employed in this study is explained. Moving forward, Section 4 encompasses the presentation of the dataset and the subsequent model development. Moreover, Section 5 incorporates a detailed discussion of the outcomes derived from the developed models. Finally, Section 6 presented the conclusions emanating from the present investigation.

## 2. Literature background

Extensive scholarly investigations have been dedicated to the investigation of the license plate recognition system, specifically in its ability to accurately identify and classify all alphanumeric characters under adverse circumstances [23–26]. To solve these problems, these studies have looked at a number of different approaches, including convolutional neural networks (CNN) [27–30], long short-term memory (LSTM) [31–33], and artificial intelligence approaches [34–36].

Al-Turjman and Malekloo (2019) conducted a thorough categorization of smart parking systems, taking into account both soft and hard design factors. They conducted a comprehensive review of the current technologies and sensors used in academic research. These systems placed particular emphasis on the importance of data reliability, security, privacy, and other crucial design considerations. The investigation examined emerging parking trends in the ecosystem, specifically focusing on data interoperability and exchange. The researchers identified unresolved research challenges in current smart parking systems and suggested a conceptual hybrid-parking model as a potential solution [37]. Liu et al., (2019) developed a deep convolutional network specifically designed for recognizing Chinese characters, letters, and numbers on license plates. This resulted from carefully examining the practical requirements of license plate recognition algorithms and thoroughly examining the fundamentals of deep convolutional networks. The purpose of their network was to automatically acquire important image features, addressing the limitations of traditional license plate recognition algorithms that rely on manual feature recognition. The experimental results supported the effectiveness of the proposed approach in quickly and accurately identifying license plate characters in complex road conditions [38]. Wang et al., (2019) introduced a new method called Multi-Task Convolutional Neural Network for License Plate Detection and Recognition (MTLPR). This method achieves higher accuracy and lower computational complexity compared to existing approaches. Furthermore, they incorporated a comprehensive dataset of Chinese license plates to facilitate

their experimental procedures. The methodology proposed entailed training a Multi-Task Convolutional Neural Network (MTCNN) for efficient license plate detection. Their proposed approach further enhances the precision of recognition. Their proposed method was compared to other advanced techniques, and the experimental results showed that it outperformed them in terms of detection and recognition accuracy as well as speed [39].

Singh and Bhushan (2019) successfully developed and implemented an expert-level Automatic Number Plate Recognition (ANPR) system that exhibits enhanced robustness in various challenging scenarios compared to previously proposed systems. They devised a robust technique utilizing deep neural networks for License Plate Detection (LPD) in images. Through rigorous experimentation, they achieved commendable results, demonstrating acceptable accuracies for both LPD and License Plate Recognition (LPR) tasks [40]. Weihong and Jiaoyang (2020) conducted a thorough discussion on the application of deep learning techniques in the field of license plate recognition. They introduced the most cutting-edge algorithms, addressing the three primary technical challenges. Furthermore, the deep learning algorithms were categorized into direct detection algorithms and indirect detection algorithms. The study involved a meticulous analysis of the strengths and weaknesses inherent in current license plate detection algorithms as well as character recognition algorithms. In addition, a comparative assessment was conducted, considering variations in data sets, computing workstations, accuracy, and processing time across different license plate recognition systems. To conclude, the researchers compared and elucidated existing public license plate datasets, taking into account factors such as the number of images, resolution, and environmental complexity. Moreover, they outlined prospective avenues for future research directions in the field of license plate recognition [41]. In another study, Pustokhina et al., (2020) introduced an efficient deep learning-based model for Vehicle License Plate Recognition (VLPR) called the OKM-CNN model. This model incorporated optimal K-means (OKM) clustering-based segmentation and Convolutional Neural Network (CNN) based recognition techniques. The OKM-CNN model operated through three key stages: License Plate (LP) detection, segmentation utilizing the OKM clustering technique, and license plate number recognition using a CNN model. To evaluate its performance, the researchers conducted an extensive experimental analysis employing three datasets, namely Stanford Cars, FZU Cars, and the HumAIn 2019 Challenge dataset. The simulation results demonstrated the superior performance of the OKM-CNN model in comparison to other methods, thereby highlighting its effectiveness in VLPR tasks [42].

Lubna et al., (2021) undertook an extensive examination of contemporary methodologies and advancements within the realm of automatic number plate recognition (ANPR) systems. Their investigation encompassed a comprehensive evaluation of diverse real-time-tested and simulated algorithms, including those that employ computer vision (CV) techniques. The primary objective of their study was to propel the current state of knowledge in Intelligent Transportation Systems (ITS) by leveraging CV algorithms in ANPR. In order to achieve this, they methodically classified these algorithms based on the requisite characteristics essential for successful recognition at each distinct stage. Ultimately, they conducted an extensive discussion concerning the existing challenges and circumstances, offering viable solutions and recommendations for future research endeavors [43]. Kaur et al., (2022) provided a comprehensive overview of the

conceptual framework and operational mechanisms of the Automatic License Plate Recognition (ALPR) system. Furthermore, their study accentuated the profound significance of ALPR technology in everyday life. They conducted an analysis of existing ALPR systems, shedding light on the challenges faced in the field. Additionally, their study delved into the specific context of ALPR systems in Asian countries, exploring the unique character recognition techniques employed in these regions. An important observation made is the absence of a standardized vehicle license plate database that can serve as a common reference for research and development. In light of this, they proposed the generation of a generic dataset that encompasses diverse license plate types, thereby enhancing the variety and breadth of available data for future investigations [44]. A new approach to vehicle identification and license plate recognition was introduced by Ammar et al., (2023). Their innovative system employed a multi-stage, real-time, deep learning-based framework that effectively integrated two object detectors, an image classifier, and a multi-object tracker to accurately identify car models and license plates. They capitalized on the information redundancy present in Saudi license plates, which contain both Arabic and English characters. Their system was optimized to achieve real-time operation on edge GPU devices while simultaneously maximizing model accuracy by capitalizing on the temporal redundancy inherent in video stream frames. To evaluate its performance, the system underwent experimental testing in real-world, unconstrained environments at various parking entrance gates, involving vehicles and license plates. Their results showed that using the proposed system to process video streams led to acceptable improvements in the relative accuracy of recognizing car models and license plates, respectively [45].

## 3. Methodology

One of the limitations encountered when employing deep learning techniques with images is the absence of a suitable database containing an adequate number of acceptable images for network training. To overcome this challenge, it becomes necessary to utilize a database with fewer basic images, which can be accomplished by augmenting the original data with dummy data during the network training process. Consequently, this study proposes a novel approach that achieves favorable results by using a smaller database while concurrently enhancing the performance of the UNet model and SRCNN model [46,47].

The primary objective of this study is to introduce a novel approach for repairing damaged points in low-resolution images by leveraging deep networks to enhance image quality and effectively inpainting damaged areas. To achieve this, a collection of Persian license plate images is gathered to construct a high-resolution image database, with the downscaled versions of these images utilized to generate the corresponding low-resolution data. To enhance the accuracy of the predicted image, data augmentation techniques are applied to augment the input images. The SRCNN algorithm is then employed to perform super-resolution (SR) operations on the low-resolution license plate images. Subsequently, the UNet algorithm is utilized to inpainting the damaged areas within the license plate images, as illustrated in Figure 1. It is important to note that the quality of the data and the number of input images directly impact the accuracy of the predicted image. However, it should be acknowledged that higher-quality data and an increased number of input images also result in longer training times for the network.

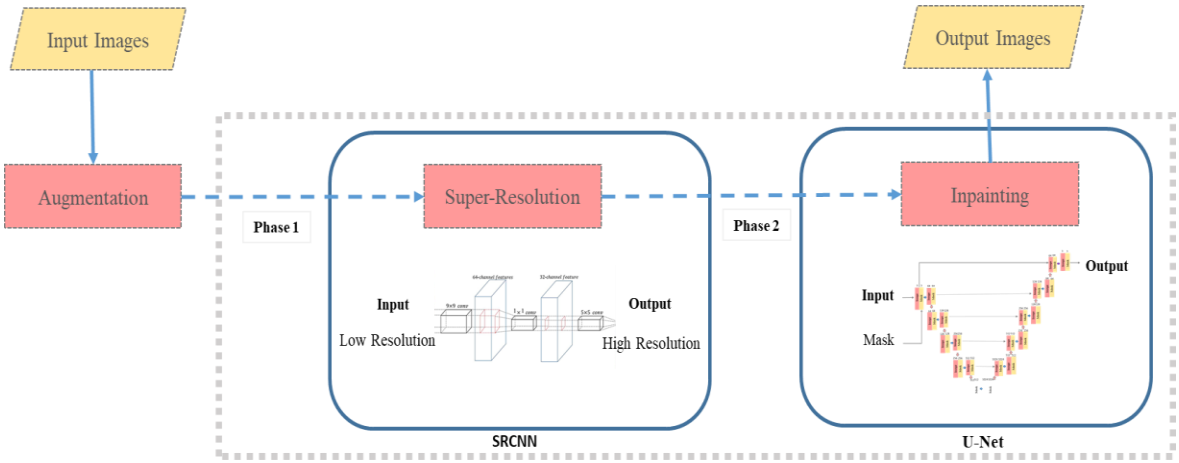


**Fig. 1.** An overview of the study process.

The underlying assumption is that neighboring pixels exhibit high similarity and can be employed to enhance image resolution and restore degraded pixels. The selection of a pixel that is in close proximity to the studied pixel is crucial for creating high-resolution images, as it reduces computational complexity and minimizes reconstruction errors. Despite these advancements, there remains a constant demand for innovative and efficient approaches to restoring lost areas within images.

## 3.1. U-Net

In inpainting algorithms, the enhancement of specific degraded pixel regions within an image is achieved through the incorporation of neighboring pixel information [48]. However, it's important to acknowledge that while these techniques are effective for image improvement, they exhibit limitations under the following circumstances:

- The encompassing areas might lack sufficient information (pertaining to pixels corresponding to degrade regions) required for completing the absent sections.
- For the reconstruction of these missing areas, it becomes necessary to deduce the object features present within the image. This is due to the fact that images constitute not merely an arbitrary arrangement of pixel values, but rather a spatial arrangement of such values.

In certain scenarios, favorable outcomes have been achieved using conventional systems for the latter challenge. Nevertheless, when these objects lack structural repetition, the process of re-inferring becomes intricate for image enhancement systems.

In contrast, humans rely on knowledge and comprehension cultivated from their experiences with the world over time. Deep learning techniques enable us to restore images. This approach adopts a learning-based paradigm where a sophisticated architecture based on deep UNet is trained to predict absent pixels. The goal is to ensure that these pixel predictions align both visually and semantically with the original image. In recent years, deep learning models have emerged as effective tools for image inpainting tasks, and one popular architecture is the UNet. The UNet architecture is an extension of the conventional Convolutional Neural Network (CNN) architecture, specifically designed for image segmentation and restoration tasks [49]. The size of

the input image is shown in terms of x and y in the input. The trajectory followed by the input image within the architecture resembles a U-shape, which leads to the nomenclature 'UNet' for this network. Within this architectural framework, every individual pixel of the image undergoes labeling. The initial segment of UNet, tasked with feature extraction and image dimension reduction via pooling, is referred to as the encoder. Subsequently, the latter half is designated as the decoder, responsible for restoring the image to its initial dimensions, along with a corresponding mask indicating the missing or damaged regions. In the UNet architecture, feature maps with dimensions of x×y are denoted as k. The activation function is applied to the value of x, setting negative values to zero while leaving positive values unchanged. Following each step of the encoder path, the max pooling operator is applied, which increases the size of the feature maps. However, this pooling operation may result in a loss of local information within the image. To mitigate this loss, concatenation operations are employed to combine feature maps.

## 3.2. Super resolution convolutional neural network (SRCNN)

Computational intelligence serves as a prevalent computational approach in numerous scientific disciplines such as transportation and road safety [50–54], geotechnics [55–58], structures [59–61], and water and sewage engineering [62–64]. Deep learning, an integral facet of computational intelligence, holds a singular and significant status in various industrial and technical sectors due to its unparalleled ability to effectively tackle complex challenges. While the inception of deep learning can be traced back to the 1980s, its practical implementation has predominantly emerged in recent years, primarily due to the demand for substantial labeled data and significant computational power [65–68]. Commonly denoted as "deep neural networks," deep learning techniques extensively rely on neural network structures. Within the realm of deep learning, a convolutional neural network (CNN, or ConvNet) emerges as a prominent deep neural network variant. Initially devised for the purpose of object detection, CNN has subsequently garnered extensive adoption across a diverse range of deep neural network applications [69–72]. These encompass multifaceted undertakings such as text identification, action recognition, classification, and regression, among others [73–77].

In the last two decades, significant progress has been made in the field of super-resolution (SR), especially by using deep learning methods. On the other hand, the methods of increasing image resolution can be categorized into single-image methods and multi-image approaches. In single-image SR, it tries to reconstruct the SR version of a low-resolution LR image by learning the content of the LR-HR image pair [78]. Meanwhile, in multi-image super-resolution (SR), the information from several scene images or frames of a video is utilized to reconstruct the details of a single image within the scene. Considering that multiple images of the scene are not always available, single-image SR is of great importance for vision applications, and several algorithms have been proposed for it in recent years. In many studies, human visual perception has been used to measure the performance of SR methods. Recently, deep neural networks have significantly improved the process of obtaining higher-quality images. Some models based on deep neural networks have been very successful in terms of reconstruction accuracy and computational performance for super image resolution. In 2016, a novel deep learning-based technique was introduced to enhance image resolution. This technique leveraged the Super Resolution Convolutional Neural Network (SRCNN) architecture, which consisted of three

distinct layers. The initial layer served as the input layer, where the low-resolution image was inputted into the network and subjected to a convolutional filter to extract pertinent features. The intermediate layer, comprising multiple convolutional layers, facilitated nonlinear transformations on the extracted features. The configuration and parameters of these convolutional layers were subject to variation based on the specific implementation. Subsequently, the output layer generated a high-resolution image. During the training phase, the SRCNN model was trained on a sizable dataset comprising pairs of low-resolution and high-resolution images. The model learned how to map low-resolution input images to their high-resolution counterparts by minimizing a loss function that measured how different the network's output was from the high-resolution image. This training process endowed the SRCNN model with the capability to enhance the resolution of low-quality images, leading to improved image quality and enhanced details.

## 3.3. Kernal

In the context of convolutional neural networks, a kernel refers to a matrix that functions as a window over the input image. As the kernel traverses the image, its values are multiplied by the corresponding elements of the input matrix, producing the desired output. The convolution operation serves as a pivotal step in convolutional networks, where each convolutional layer applies a kernel to the input image, generating a filtered output. This mechanism enables the network to capture the influence of neighboring pixels and retain spatial information.

By using convolutional layers with kernels, the network becomes good at learning the most important parts of an image and pulling out the information it needs to do its job. Furthermore, the utilization of kernels aids in reducing the number of trainable parameters in the network, enhancing its efficiency, and facilitating the training process.

Overfitting arises when the model becomes excessively intricate and begins to fit the noise present in the training data rather than capturing the underlying pattern. Kernel regularization serves as a remedy to this issue by incorporating a penalty term into the objective function being optimized by the algorithm. This penalty term encourages the algorithm to discover a simpler decision boundary, thus fostering better generalization to unseen data. Fine-tuning intricate neural networks can expedite the training process and facilitate faster convergence, leading to the development of a more versatile model. The process of fine-tuning entails taking a pre-existing neural network that has been trained on a different task and adjusting its parameters to suit a new task or dataset. This approach is particularly advantageous when working with limited training data or when confronted with a closely related task. By capitalizing on the prior knowledge encoded within the pre-trained network, fine-tuning mitigates the time and effort required to train a new model from scratch.

In computational models, there are three common types of kernel regularization [79]: L1, which changes the sum of absolute values of the weights; L2, which shifts the absolute values of the weights; and L1L2, which changes both the sum of absolute values and the squared sum of the weights. The focus of this study was on L1 regularization. L1 regularization is specifically advantageous for handling high-dimensional datasets. Eq. 1 for the regularized kernel function is defined as follows:

$$K'(x_i, x_j) = K(x_i, x_j) + \lambda . I \quad (1)$$

$K(x_i, x_j)$ represents the original kernel function that computes the similarity between two data points. λ is the regularization parameter, controlling the strength of regularization. A higher λ leads to stronger regularization. I is the identity matrix. The regularization term λ* I is added to the original kernel matrix. This makes it so that individual data points have less of an effect on the decision boundary, which stops the model from fitting too well.

It aids in reducing the feature quantity utilized in the computational model. This is accomplished by incorporating a penalty term into the objective function, which is directly proportional to the absolute value of the weights. Such an adjustment incites sparse weight vectors, leading to a significant number of weights being nullified.

## 4. Modelling

In this paper, we employ evaluation methodologies: Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM) [80,81].

The mean square error is a technique used to measure the magnitude of error, representing the variance between actual values and their estimated counterparts. This criterion consistently produces positive values, distinct from zero. The proximity of this index to zero directly correlates with diminished error levels. The mean square error from a collection of 'n' data points can be computed employing Eq 2 [82]:

$$MSE = \frac{1}{mn}\sum_{i=1}^{n-1}\sum_{j=1}^{m-1}(Y_{ij-}\hat{Y}_{ij})^2 \quad (2)$$

Where m and n are the number of pixels in the length and width of the image, $Y_{ij}$ is the original image and $\hat{Y}_{ij}$ is the estimated image. Next, PSNR is easily defined through the mean squared error MSE as Eq 3:

$$PSNR = 10\log_{10}(\frac{{MAX_I}^2}{MSE}) \quad (3)$$

Where ${MAX_I}^2$ is the maximum possible pixel value of the image.

Another criterion of consideration is the SSIM, a metric designed to assess the structural resemblance between two images by leveraging the inherent structure of the original images. Within the structure of the original images, the behavior of pixels is intricately linked with that of their neighboring pixels, encapsulating crucial insights into the object structure within the image. The computation of SSIM involves evaluating the degree of structural similarity within the vicinity of each individual pixel. This process is encapsulated by Eq 4:

$$SSIM(I.\hat{I}) = \left(\frac{2\mu_I\mu_{\hat{I}}+C_1}{\mu_I^2+\mu_{\hat{I}}^2+C_1}\right)^{\alpha} \cdot \left(\frac{2\sigma_I\sigma_{\hat{I}}+C_2}{\sigma_I^2+\sigma_{\hat{I}}^2+C_2}\right)^{\beta} \cdot \left(\frac{\sigma_{I\hat{I}}+C_3}{\sigma_I\sigma_{\hat{I}}+C_3}\right)^{\gamma} \quad (4)$$

In this context, $\mu_I$ and $\sigma_I$ represent the mean and standard deviation of the original image, while $\mu_{\hat{I}}$ and $\sigma_{\hat{I}}$ correspondingly denote the mean and standard deviation of the estimated image. Furthermore, $\sigma_{I\hat{I}}$ signifies the mutual correlation between the two images, denoted as $I$ and $\hat{I}$.

Introducing α, β, and γ as coefficients governing the weighting of each respective function, the constants $C_2$, $C_1$ and $C_3$ characterized by their small positive values, play a crucial role in averting computational instability. These constants prove indispensable, particularly when the denominator of a fraction assumes a diminutive value.

## 4.1. Dataset

In this research, license plate images were utilized as the dataset, specifically 4171 Persian license plate images with an initial size of 64x64 pixels. From this dataset, low-resolution input images were created. Educational images were acquired from a competition database for the enhancement of distorted license plate images hosted at Amirkabir University [83]. Each of the images in the dataset had a unique resolution and different dimensions, which is considered a suitable case for studying the challenge of increasing the resolution and repairing the damaged areas. The dataset was divided into three parts: training data, validation data, and testing data, with proportions of 60%, 20%, and 20%, respectively. The number of images of each of them in Table 1 has been reported.

**Table 1**
Quantity of images.

| | Image percentage quantity | Image quantity |
|---|---|---|
| Training data | 60% | 2503 |
| Validation data | 20% | 834 |
| testing data | 20% | 834 |

To enhance the input images, random transformations were applied. These transformations included random rotations within the range of (0, 50), random shifts to the width and height of the image within the range of (0, 0.2), and random magnification applied to the image within the range of (0, 0.3). To create a dummy dataset of images, these three factors randomly affected each image. This augmentation significantly improved the network's ability to handle random transformations, both dependent on and independent of the image [84]. The SRCNN was employed in the research. The SRCNN initially reduced the image quality by applying a factor of 0.5, resulting in half the resolution of the original input image. However, in the output images, high-resolution images were obtained. This approach of reducing image dimensions and subsequently increasing resolution is commonly used in existing methods. A database of high-resolution reference images was necessary for evaluating the methods. In the next step, the U-Net model was utilized to perform inpainting by applying a mask to the images. The subsequent sections will elaborate extensively on the intricacies of the modeling process.

## 4.2. Partial convolution layer

Throughout the process of inpainting, the partial convolution layer is effectively utilized, encompassing two primary procedures: the partial convolution operation and the mask update operation [48]. These procedures are employed to compute the pixel update operation following each iteration of mending the impaired region. The partial convolution operation entails the calculation of the convolution between the undamaged pixels and a trainable kernel, while the damaged pixels are substituted with zeros. Conversely, the mask update operation modifies the

binary mask that identifies the damaged areas, assigning a value of 1 to each pixel in the mask if it corresponds to an undamaged pixel in the current or any previous iteration and 0 otherwise.

Eq 5 is the mathematical representation of the complexity that the partial convolution layer exhibits at each pixel location.

$$x' = \begin{cases} W^T(X \odot M)\frac{sum(I)}{sum(M)} + b. & if\ sum(M) > 0 \\ 0 & otherwise \end{cases} \quad (5)$$

Eq 5 encapsulates the intricate relationship between the convolutional kernel, the binary mask, and the input image, serving as a means to determine the output of the partial convolution layer at each pixel location. By employing this equation, the partial convolution layer adeptly rectifies the damaged regions within an image, while upholding the visual coherence and consistency of the surrounding areas.

In Eq 5, the variable X signifies the feature values, while W represents the weight associated with the convolutional filter. The bias term is denoted by b. The $\odot$ symbol denotes element-wise multiplication, and the matrix I possesses the same dimensions as the matrix M. However, all elements of matrix I are uniformly set to 1. Furthermore, the output values solely rely on the unmasked inputs. To appropriately adjust the variable value of valid (unmasked) inputs, a scaling factor of $\frac{\mathrm{sum(M)}}{\mathrm{sum(I)}}$ is applied.

Subsequent to each partial convolution operation, the mask is updated utilizing Eq 6:

$$m' = \begin{cases} 1 & if\ sum(M) > 0 \\ 0 & otherwise \end{cases} \quad (6)$$

Eq. 6 facilitates the process of updating the binary mask by assigning a value of 1 to each pixel that remains unmasked in the current iteration or any previous iteration. Conversely, if a pixel is consistently masked across all iterations, its corresponding value in the updated mask will be 0. By updating the mask over and over again and then running partial convolutions, the algorithm is able to fix the damaged parts of an image while keeping the integrity and visual harmony of the rest of the image (Fig. 2).

## 4.3. SRCNN modelling for super resolution

The model architecture utilized in this study comprises three convolutional layers, each characterized by specific numbers of filters and kernel sizes. The initial layer encompasses 64 filters with a kernel size of 9x9, while the second layer encompasses 32 filters with a kernel size of 1x1. Subsequently, the final layer incorporates three filters with a kernel size of 5x5 (Figure 3). The Rectified Linear Unit (ReLU) activation function is applied to the first two layers, whereas the last layer utilizes a linear activation function. Additionally, kernel regularization is incorporated into all layers. In the context of image resolution enhancement algorithms, kernel regularization plays a crucial role in diminishing noise and artifacts that may arise during the image upscaling process. By introducing a penalty term to the kernel weights, the algorithm encourages the model to acquire smoother filters that yield more visually pleasing and natural-looking images. The "same" padding parameter is employed for all three layers, ensuring that the

output size of each layer matches the input size. This is accomplished by padding the input image with zeros along its edges. The primary purpose of this padding is to preserve the spatial dimensions of the image throughout the convolutional process, thereby preserving the image quality.

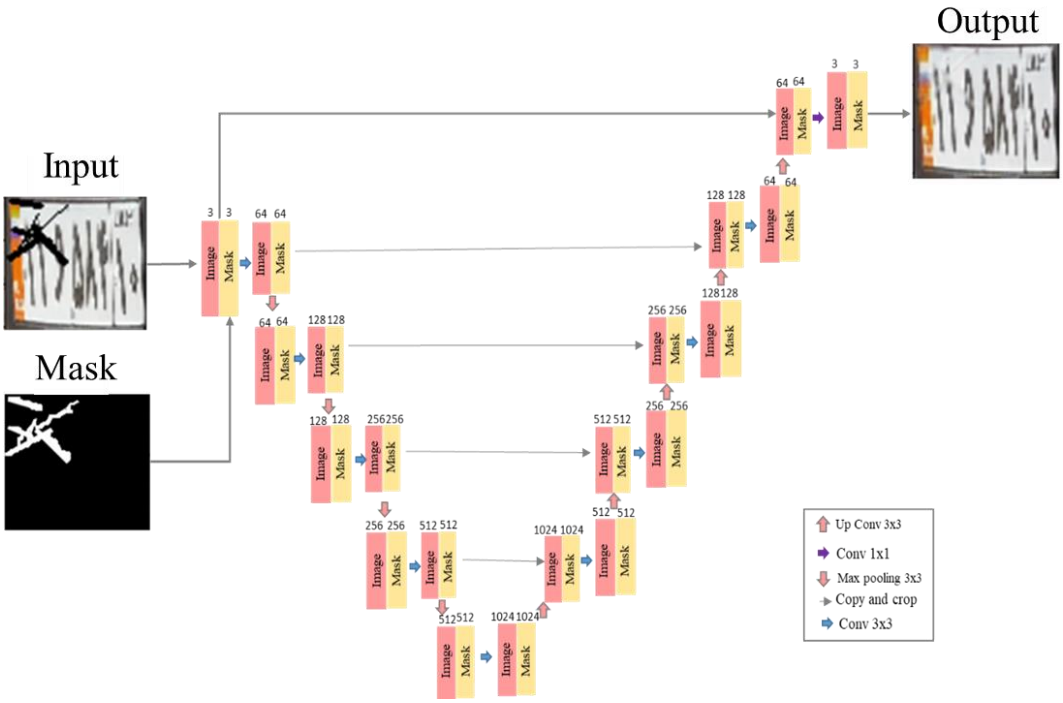


**Fig. 2.** The model architecture of U-Net.

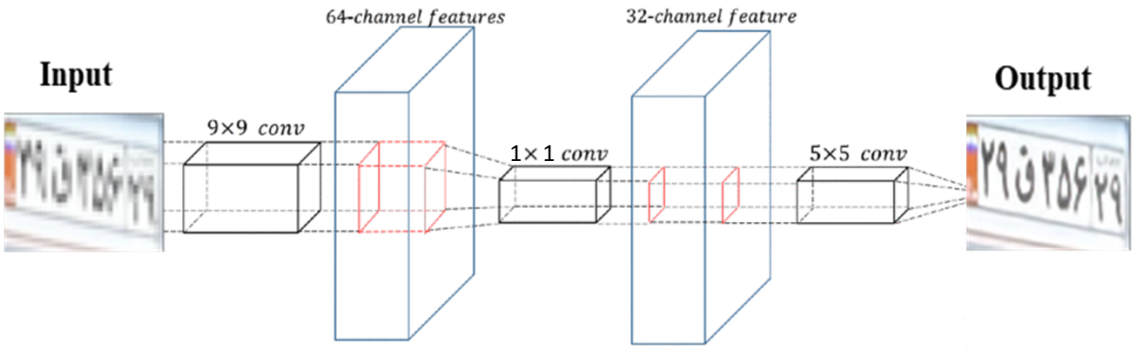


**Fig. 3.** The model architecture of SRCNN.

## 5. Results and discussion

In this research, we introduced a proposed approach for augmenting image resolution by employing a network built upon the SRCNN architecture. The network architecture consists of three layers, which are instrumental in enhancing the resolution of the input image. Additionally, to restore lost regions within the image, we devised a UNet-based network featuring five encoder layers and five decoder layers. However, a potential drawback of the resolution increment and reconstruction process is the potential blurring of the image. To overcome this challenge and

enhance the algorithm's effectiveness, we introduced a kernel regularization technique at every layer of the network. This technique aims to mitigate blurring artifacts and enhance the overall performance of the algorithm.

During the training phase, the SRCNN model was trained using a dataset comprised of low-resolution images derived from high-resolution counterparts. Similarly, the UNet model was trained on a dataset consisting of damaged images created from pristine images. The training process involved 20 epochs with a learning rate of 0.0002. In order to simulate real-world scenarios where images may have missing or impaired regions, we generated random masks containing irregular lines for training the image enhancement algorithm. Overall, our proposed approach has demonstrated promising outcomes in enhancing image resolution and restoring damaged regions. By using the SRCNN and UNet models and integrating kernel regularization and data augmentation techniques, the quality and sharpness of the resulting images were enhanced while preserving their inherent natural appearance. The comparison of the obtained results is shown in Table 2. Also, Figs 4 to 5 show the results of inpainting and super resolution, respectively.

**Table 2**
Comparison of results of inpainting and super resolution models.

| | Inpainting | | Super Resolution | |
|---|---|---|---|---|
| | U-Net | U-Net with kernel regularizer | SRCNN | SRCNN with kernel regularizer |
| SSIM | 0.8333 | 0.8564 | 0.8513 | 0.8728 |
| Peak SNR | 22.3879 | 29.1371 | 25.2102 | 27.4512 |
| SNR | 13.7155 | 17.8241 | 21.9786 | 23.2893 |
| Loss | 0.5221 | 0.4020 | 0.0024 | 0.0018 |
| Accuracy | 0.7132 | 0.7919 | 0.8466 | 0.8501 |

In conclusion, the IoT parking system based on the concepts discussed in this study holds great potential for improving parking management and enhancing security. The suggestions provided offer valuable directions for future research endeavors in this field. In addition, it is possible to draw the following conclusions:

To enhance the efficacy of the proposed algorithm when dealing with images depicting diverse conditions, it is recommended to explore alternative solutions and pre-processing techniques. This exploration can help optimize the algorithm's performance and ensure accurate identification and analysis of parking-related data. Furthermore, the utilization of alternative machine learning algorithms for training the system can contribute to improved image quality, clarity, and overall accuracy. Investigating different algorithms and their suitability for the IoT parking system can lead to advancements in image processing and recognition capabilities. The application of deep learning algorithms for restoring damaged regions on Persian license plates demonstrates promising potential in terms of computational efficiency. However, the dependency of License Plate Recognition (LPR) algorithms on processing power can result in extended image analysis times. To overcome this limitation, it is imperative to allocate robust hardware resources to the system. This includes ensuring sufficient computational power and optimizing the system's architecture to handle higher pixel counts for enhanced image resolution.

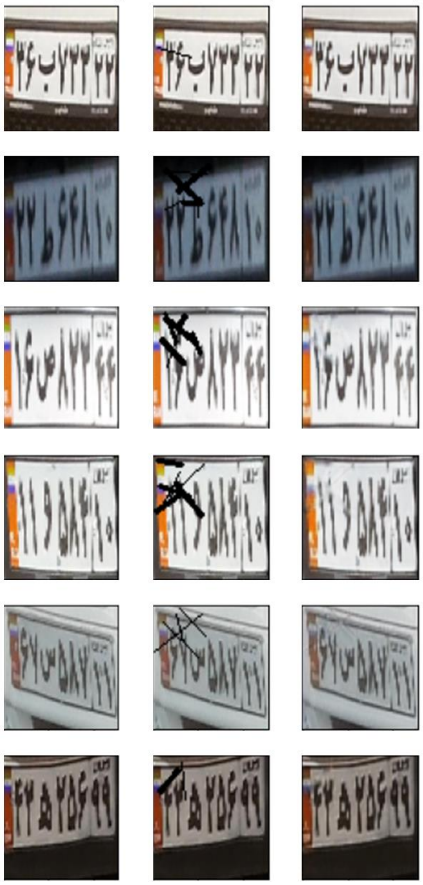

**Fig. 4.** The results of U-Net with kernel regularizer model for inpainting.

**Fig. 5.** The results of SRCNN with kernel regularizer model for Super-Resolution.

This method is particularly useful when there is a need to identify or verify a license plate, but some characters have been altered deliberately. In such cases, the method involves analyzing the remaining visible characters and attempting to reconstruct the original plate information. However, it's important to note that this method has its limitations. If the installed license plate on a vehicle actually belongs to another car, the complexity of the identification process increases. In such instances, it becomes necessary to tap into a more extensive data source that includes not only the partial or altered license plate information but also additional details such as the color and model of the car. Expanding the data source to include these additional parameters enhances the accuracy of the identification process. The color and model information contribute significantly to narrowing down the possibilities and increasing the chances of correctly associating a license plate with the corresponding vehicle. This holistic approach takes into account multiple variables, making the identification process more robust and reliable. In summary, while the method of reconstructing a license plate from partial information is effective in cases of intentional alterations, a broader data source is essential when dealing with situations where the license plate installed on a vehicle does not match its actual registration. This comprehensive approach, encompassing not only the license plate details but also the color and model of the car, provides a more thorough and accurate means of identification in scenarios where intentional mismatches may occur.

Future research efforts should focus on optimizing the proposed algorithm's performance, exploring advanced pre-processing techniques, and evaluating the feasibility of incorporating additional vehicular attributes. Real-world experiments and evaluations in different parking scenarios can provide valuable insights into the system's effectiveness, reliability, and practicality. With continued research and development, the IoT parking system has the potential to revolutionize parking management, increase efficiency, and enhance security in urban areas. By addressing the recommendations and further investigating the suggested areas, researchers can contribute to the advancement and successful implementation of IoT-based parking systems.

## 6. Conclusions

The rise in population and urbanization has led to a surge in the number of vehicles, posing security concerns and parking challenges. Advanced artificial intelligence systems have shown remarkable capabilities in license plate identification and retrieval, making them crucial for the efficient management of smart parking facilities. This cutting-edge technology has the potential to improve smart parking management and address parking-related issues. By employing automated license plate recognition, the time spent searching for suitable parking spaces can be minimized, expediting the parking process. In the accomplished research, a novel approach for the identification of Iranian vehicle registration plates was put forth, leveraging two techniques: Digital Inpainting and Super Resolution, in tandem with the UNet and SRCNN computational models. A robust dataset, comprised of 4171 unique examples of Iranian registration plates, served as the empirical basis for gauging the efficacy of the proposed models. A plethora of performance indicators were employed to discern the capabilities of the models. The UNet model, which gained strength from the addition of a kernel regularizer, displayed a favorable level of accuracy, posting a score of 0.79. In a parallel vein, the SRCNN model, augmented with

a kernel regularizer as well, displayed praiseworthy accuracy, achieving a score of 0.85. For subsequent studies, it is advised to delve into other deep learning methodologies, like the long-short-term memory (LSTM) network, with an eye towards enhancing operational efficiency. Furthermore, the incorporation of these deep learning methodologies with meta-heuristic algorithms, for instance, the gray wolf and Whale algorithms, could potentially engender elevated results. The performance evaluation of such amalgamations presents a promising prospect for future scholarly exploration.

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## Conflicts of interest

The authors declare no conflict of interest.

## Authors contribution statement

Conceptualization; N.S. and S.S.H.; Data curation; N.S.: Formal analysis; N.S: Investigation; N.S. and S.S.H.: Methodology; N.S. and S.S.H.: Software; N.S.; Supervision; G.G. and V.A: Validation; N.S.; Writing – original draft; N.S. and S.S.H.; Writing – review & editing; N.S, S.S.H, GG.

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